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Comparing Functional Analysis Methods for Product Dissection Tasks

The purpose of this study is to begin to explore which function identification methods work best for specific tasks. We use a three-level within-subject study (n = 78) to compare three strategies for identifying functions: energy-flow, top-down, and enumeration. These are tested in a product dissection task with student engineers who have minimal prior experience. Participants were asked to dissect a hair dryer, power drill, and toy dart gun and generate function trees to describe how these work. The function trees were evaluated with several metrics including the total number of functions generated, the number of syntactical errors, and the number of unique (relevant and nonredundant) functions. We found no statistical, practical, or qualitative difference between the trees produced by each method. This suggests that the cognitive load for this task for novices is high enough to obscure any real differences between methods. We also found some generalized findings through surveys that the most difficult aspects of using functional decomposition include identifying functions, choosing function verbs, and drawing the diagram. Together, this may also mean that for novice engineers, the method does not matter as much as core concepts such as identifying functions and structuring function diagrams. This also indicates that any function identification method may be used as a baseline for comparison between novices in future studies. [DOI: 10.1115/1.4030232]

1 Introduction

Functional decomposition is a process that is typically used to assist engineers with identifying essential functions in various design tasks, including product dissection. It is an important tool used in industry to improve legacy products, understand competitor products, or help new employees learn about a company design. More generally, it is a type of problem solving strategy used by engineers to convert complex problems into abstractions [1], where they are easier to solve [2,3]. The ability to do this effectively represents a high-level skill and deep learning [4]. However, functional decomposition is often ignored by engineers because it is perceived as being too easy, too hard, or not important [5]. This may simply be because engineers use design methods opportunistically [6], are taught conflicting definitions of “function” [7], or find competing claims to the “right” approach [8]. One approach to improving adoption is educating engineers as to when and why functional decomposition is most effective.

While prior literature explores why functional decomposition is important, there is virtually no discussion of when proposed methods are best for various tasks. These include early design, product dissection, reverse engineering, and modeling. In addition to task, there are several other parameters that have not been explicitly studied. These include the level of expertise, the level of training, the diagram type, and the strategy used to discover functions (see Table 1). This paper contributes the first comparative empirical study of different identification methods, as well as defined parameters by which other studies may be compared to this one. It also offers some insight into why functional decomposition may be difficult for novice engineers to understand and adopt [5].

The primary focus of this study is the difference between methods used to identify functions in product dissection tasks. The methods found in this study correspond with common methods taught in design text books and found in industry [9]. Accordingly, we keep the other parameters constant, including using the same type of function diagram for each identification method. This paper will describe the experimental design to test these methods. We report quantitative, mixed-methods, and qualitative results, and offer interpretations of these results.

1.1 Definitions. We define functions as “the solution-neutral (or embodiment-neutral) detailed description of what are the intentions for the products” [10]. When we use the term “method,” we mean the strategy an engineer uses to identify a function. Energy-flow is defined as tracing material, information, and energy flows through a device and mapping functions to changes in these flows. Top-down is defined as the process of determining the overall function, followed by decomposing this into subfunctions, and continuing until functions are defined on the part level. Enumeration is defined as writing out whatever functions come to mind, with no specific strategy for identifying them. We consider these methods as independent of the diagram used to record the functions [9].

“Functional analysis” is used to mean the process of identifying functions for an already existing artifact or concept [1] (i.e., reverse engineering or dissecting products). “Functional synthesis” is defined as identifying functions in design where no artifact or embodiment exists (i.e., pre-ideation). We consider synthesis and analysis to be two different types of problem solving [11], and their related tasks to be unique types of problems [12]. Additionally, we agree that there is no single, correct function structure for synthesis or analysis [13,14]. Hence in this paper, “functional decomposition” describes both synthesis and analysis.

2 Background

Experimental findings by Eckert et al. found that engineers tend to use an energy-flow, top-down, or enumeration strategy for identifying functions in an unknown product, with some minor variations. Additionally, the participants in their study tended to analyze only as much as they needed, often mixing methods to

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Table 1 Parameters used by this study and the levels chosen for the study, in gray

Eng. expertise	Training	Scale	Complexity	Strategy	Diagram type	Design task
Novice	None	Component	Low	Enumeration	Function Tree	Product dissection
Graduate	Introductory	Product	Medium	Energy-flow	Function-means	Reverse engineering
Professional	Some	System	High	Top-down	FFBD	Ideation
Expert	Practiced			Bottom-up	Flow-chart	Eng. modeling
	Expert				List	FMEA
					FAST	Cost allocation

suit their purposes [9]. Consequently, we searched design text books (Table 2) and literature to find what function identification methods are taught. We assume that there is a core set of principles to decomposition that accepts multiple definitions of function and implementation, but ignores methodological differences between them [7]. We organized the methods in literature into three groups based on the identification methods in Eckert et al. [9]: energy-flow, top-down, and enumeration (see Table 2). One text included a method which did not fit in our classification scheme [10]. While this method is not considered in this study, we explored it in a separate paper [11].

2.1 Methods Found in Literature and Usage. The most common method found in the literature search was the "energy-flow" approach, sometimes called "black-box" [1,14,15–19,21]. This method is unique from the top-down and enumeration approaches because it primarily focuses on "horizontal" relationships between functions and explicitly considers material, energy, and information flows through a system [29]. Most authors recommend creating multiple flow diagrams, each at a different level of abstraction. In a function tree, each flow diagram constitutes a single level of the function tree. Some versions of the "black-box" approach do not emphasize the types of flows and instead focus on steps in a process.

The second most commonly described method was enumeration [15,24–28]. In these citations, the authors gave no specific direction regarding how to identify functions other than to simply list them out. Various sources pair enumeration with a list, function tree, or function-means tree.

The least commonly described method was the "top-down" approach [13,15,23]. This method works by selecting the top-most function and breaking each function down into relevant subfunctions. This method explicitly explores the "vertical" relationships between functions, and thus aims at recording hierarchical information [29]. This approach is sometimes paired with structure diagrams as a function-means tree. These hybrid diagrams seem to be used for design tasks only [15,30], but could potentially be used to describe a product.

One textbook describes a method called the "subtract and operate method" [22], though we identify this as the "bottom-up method" due to its similarities to the heuristic of the same name. This method is considered opposite to the top-down method, but considered to produce the same results [22,31]. Bottom-up asks engineers to consider the individual functions of parts. The bottom-up method is not examined in this paper. In another paper, we found that the cognition between the bottom-up and the methods in this paper appears to be different [32].

The majority of these texts describes functional decomposition as a step prior to concept generation. However, the same methods are sporadically applied to other design activities, such as reverse engineering (see Table 2), task analysis and failure modes and effects analysis [17,28], functional allocation [14], axiomatic design [27], and cost analysis [19]. The terminology used between all these sources is also inconsistent. For example, the terms "functional decomposition" and "functional analysis" are sometimes used to refer to a design task only [16,17,21,26–28], a reverse engineering or product dissection only [23–25], or both [1,13–15,18]. In another example, some authors use "reverse engineering" and "product dissection" interchangeably [15,18], whereas others do not [24].

Table 2 Engineering design textbooks and their treatment of functional decomposition

Authors	Method	Reverse eng.	Design	Wording used in text
Dym and Little [15]	Energy-flow	x	x	Black boxes/transparent boxes
Ulrich and Eppinger [14]		x	x	Functional decomposition
Cross [16]			x	Functional analysis
Stoll [17]			x	Functional analysis/decomposition
Ullman [18]			x	Functional modeling/decomposition
Pahl and Beitz [1]		x	x	Establish function structures/analysis of existing systems
Ullman [18]		x		Product decomposition
Dieter [19]			x	Functional decomposition
Dieter and Schmidt [20]			x	Functional decomposition
Hyman [21]			x	Functional analysis
Otto and Wood [22]		x	x	Functional modeling
Dym and Little [15]	Top-down		x	Function-means tree
Cunniff et al. [13]		x	x	Functional decomposition/reverse eng.
Phillips [23]		x		Functional decomposition
Otto and Wood [22]		x	x	Function trees
Dym and Little [15]	Enumeration	x	x	Enumeration of functions
Dym and Little [15]		x		Reverse engineering/dissection
Horenstein [24]		x		Reverse engineering
Sheppard [25]		x		Mechanical dissection
French [26]			x	Functional analysis
Magrab [27]			x	Functional analysis/decomposition
Priest and Sánchez [28]			x	Functional allocation
Otto and Wood [22]			x	the FAST method
Otto and Wood [22]	Other		x	the subtract and operate

Only a few authors cite more than one method, and only two of the books we reviewed identified all three [15,22]. These two are also among the few to describe more than one type of function diagram. We also note that between texts, the diagram type recommended for an identification method is not always consistent. In all, this seems to speak to the several traditions surrounding functional decomposition [8].

2.2 Related Work. Significant past work has focused on improving the energy-flow method. Examples of this research focus on improving taxonomy structures [33,34], the functional basis [35], and instructional methods [36]. Several studies have compared functional decomposition with axiomatic design [30], explored functionality in bio-inspired design [37], or applied functional decomposition techniques to analogical design [38]. However, to the best of our knowledge, there are no empirical studies comparing energy-flow, top-down, and enumeration for product dissection. We also failed to find studies that test which methods are best suited for other tasks [39].

3 Methodology

This study aimed to evaluate which methods are most effective for product dissection. Product dissection is used in industry and academia to understand new or competitor products or help new employees learn about a company design. However, for the purposes of this study, "most effective" is defined as providing the best understanding to a student of how a device works. This led to our first research question. We developed our second question to understand what is most difficult for engineers about the process. We explore this question to build on prior efforts in teaching functional decomposition [36]. This question is also important because industry adoption remains low [5]:

(1) Which functional decomposition methods are most effective for students?
(2) Which aspects of functional decomposition in general prove to be most difficult for students?

Several metrics are used to approximate if students understand how something works. The number of functions is used as a proxy for the level of detail a student used to examine a device. The number of unique functions is used to approximate how comprehensive the understanding was. Other metrics are used to explore function tree shape and errors, which give an approximation of understanding of the method itself.

3.1 Design of Experiment (DOE). In order to answer the first research question, we used an explanatory sequential mixed-methods approach [40] where each participant would create a function tree based on the given artifact. To maximize the use of the students, we used a three-level, within-subject DOE (i.e., 3×3 Latin square), where each student used a different method on each artifact. This DOE is common in product comparison studies [41] and has the advantage of multiplying the number of samples. It also reduces the effect of uncontrolled variables, such as self-selection bias [42]. One negative effect of this experimental design is that some effects are conflated. In this case, effects due to the product dissected are conflated with the session number. This means that in the statistical analysis, we cannot distinguish learning effects from those due to the product.

The first research question was then converted into four alternate hypotheses, below. Due to the prior literature, we expected the top-down method to have more vertices on each tree level, and generally larger function trees, as measured by geodesic distances (GDs) and total number of vertices. However, we expected the energy-flow strategy to have more unique functions and fewer errors. We also expected the enumeration method to have the fewest unique functions. Finally, we expected to see better results from participants who were a higher class level or had prior experience with functional decomposition. These and other metrics are described below in Sec. 3.5, with a detailed description of the "unique function" metric in Sec. 3.5.2:

- H0: there is no difference between the energy-flow, top-down, and enumeration methods
- H1: there is a difference between the energy-flow and top-down methods
- H2: there is a difference between the energy-flow and enumeration methods
- H3: there is a difference between the top-down and enumeration methods
- H4: the more experienced students will perform better than the less experienced students

3.2 Procedure. Participants were asked to dissect three products (see Fig. 1). All groups dissected the same product for the same session. For example, all participants dissected a power drill for their second session. For each product, they used one of three methods for determining the functionality of those products. Each student ended up using all three methods (see Table 3). The purpose of dissecting products was to help students learn "how it works" (point 1, in Ref. [5]). All sessions were held on Thursdays and group A met at 9:30 a.m., group B at 11:30 a.m., and group C at 1:30 p.m. each week.

Each session followed these steps:

(1) (2 min) Introduction, explanation of the task, and handing out presurvey (first session only) and instruction materials (every session),
(2) (6 min) Description of what a function is and instructions on how to create a function tree,
(3) (7 min) Instructions on how to use the function identification method assigned for the session, followed by an example of the method using a simplified lobe pump drawing,
(4) (45–60 min) Time for students to individually disassemble product and create function tree,
(5) (20 min) Turn in function trees, return to course instruction (product description), reassemble products, and complete a postsurvey.

In addition to instruction on how to make a function tree, students were also instructed to make a rough draft. For energy-flow, they were told to map out the energy, information, and material flows in a flow diagram on a rough draft, and to recursively break each function into subfunctions [1]. They were told to place these functions into a tree diagram. For enumeration, students were instructed to list out the functions and then organize these into a tree, while also filling in gaps. For the top-down method, they were told to identify the overall function and then break each parent function into children functions.

In order to ensure consistency between instructions in each session, we provided written instructions on how to accomplish these steps. These described what a function is, how to create a function tree, an example function tree, instructions on how to use each method, and instructions on how to convert their rough draft into a function tree. Students were also provided with the pruned function verb list [33] to aid them when choosing verbs for their functions.

3.3 Population. Participants were selected based on their participation in a product dissection class at Purdue (ME 297). The class focuses solely on product dissection in 2 hr lab sessions. Participants were told that the research activity would help them prepare for the final project in the class, where they have to describe how a product of their choosing works.

Each group consisted of varying numbers of participants due to how scheduling for the class was conducted. Group A had 8 participants; group B had 12 participants; and group C had 6 participants. Over all sections, ten students identified as sophomores, eight as juniors, and seven as seniors with one not reporting and

Fig. 1 A hair dryer, power drill, and toy dart gun

Table 3 Experimental layout by group

	Session 1	Session 2	Session 3
	Dryer	Drill	Dart gun
Group A	Top-down	Energy-flow	Enumeration
Group B	Enumeration	Top-down	Energy-flow
Group C	Energy-flow	Enumeration	Top-down

no freshmen, although the class is open to them. All participants were studying mechanical engineering.

3.4 Independent Variable—Identification Method. The independent variables used were chosen due to their common usage by engineering professionals [9]:

- Energy-flow: identify the flow of energy, mass, and information through a system. Each transformation of these flows is a function. This should be done separately on various levels before constructing a tree, breaking each function into a group of functions.
- Top-down: start with the highest level of abstraction (the whole machine) and determine overall function. Break down into subsystems and determine functions of each of these systems. Iteratively become more detailed for each level. Write these functions into a tree.
- Enumeration: write down relevant functions as they seem appropriate in whatever order they come to mind. Organize these into a tree. Participants were told that the name of this method was "important things first" [9].

3.5 Dependent Variables. Appropriate metrics for this study were drawn from prior studies (Table 4). We added a unique functions metric to this set to measure the comprehensiveness of each tree and replaced one metric (M2) with two: the average and maximum GDs. We did not include other graph metrics due to lack of relevance for hierarchies. We did not use the metrics used by Nagel et al. [36], since these are specific to the energy-flow process only. We also did not use the standard function taxonomy [35], since it is limited to energy-flow only [46] and it is intended for generating machine-readable diagrams, rather than evaluating natural-language data [47].

Table 4 Metrics used in prior research on functional decomposition

Name	Metric type
Conformance metric [43]	Raw count (M1)
Exact/approximate scoring [33]	Raw count (M1)
Unit of information [44]	Raw count (M1)
# spoken functions [10]	Raw count (M1)
# levels of abstraction [10]	Qualitative
# levels of hierarchy [10]	Tree depth (M2)
# func. on a hierarchy level [10]	Branch width (M3)
Completeness of func. analysis [10]	Raw count (M1)
Rubric (energy-flow only) [36]	Error count (M4)
# parts exposed [45]	Raw count (M1)
# same features [45]	Raw count (M1)

The dependent variables are related to prior metrics (from Table 4) and include:

- Vertices (M1): the total number of phrases on a diagram, all of which are treated as functions.
- Number of unique functions (Uniq. Func.): the number of nonredundant phrases in a diagram. More details below.
- Tree efficiency (efficiency): the ratio of unique functions to vertices. This shows how much of the tree is nonredundant.
- Maximum GD (MGD, M2): the largest of all the shortest paths in the diagram. More details below.
- Average GD (AGD, M2): the average of the shortest paths between all nodes in the diagram. More details below.
- Number of syntax errors (Errors, M4): the number of phrases left blank or not written as a verb-phrase. More detail below.
- Error ratio: the ratio of errors to vertices.
- Number of vertices on a hierarchy level (Func. Lvl. X, M3): the number of phrases on each hierarchy level.
- Perceived usefulness of activity (Survey): student responses of how useful each method was on a scale of 1 (low) to 10 (high).

3.5.1 GD Metrics. The combination of the average and maximum GDs measures the "flatness" and "bushiness" of the trees. A pair of low GDs indicates flatness, and a pair of high GDs indicates bushiness. These metrics allow us to distinguish between flat and bushy trees whereas simply counting the number of levels in a tree does not (Fig. 2). This metric is also meaningful for nonhierarchical diagrams, such as network maps, where the number of levels is meaningless (Fig. 2). A few diagrams in our dataset had nodes with more than one parent, making them no longer "trees." These metrics are robust to these irregularities. Finally, using two metrics instead of one allows us to distinguish between two tree geometries when one of the two metrics is shared (Fig. 3).

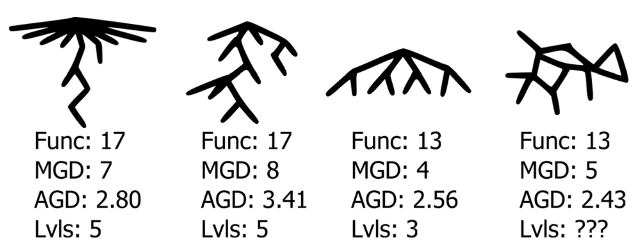

Fig. 2 The pair of GD metrics (AGD and MGD) is lower for the flat tree than for the bushy tree, even when the number of tree levels is the same. This approach is also robust to nonhierarchy diagrams.

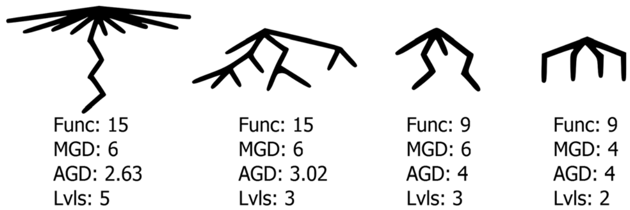

Fig. 3 The pair of GDs (AGD and MGD) is still lower for the flatter trees even when one of the two is the same

3.5.2 The Syntax Errors Metric. Measuring syntax errors is a convenient, objective way to indicate phrases that are not functions. It is an approximation, but is not subject to bias due to qualitative judgments. We found that nodes with syntax errors reliably correspond with other types of information such as design requirements, user actions, or part names. Errors include phrases that begin with an adjective (C3.3.2, Table 5), a noun (C1.3.1, Table 5), or other nonverb parts of speech. We also counted phrases beginning with generic verbs such as "to provide" or "to be" as errors. Only 1.00% of phrases coded as a syntax error were actually functions.

In conducting this analysis, we first used WORDNET in PYTHON to calculate tokens and parts of speech. Since WORDNET defaults to nouns rather than verbs, we then manually corrected the output based on our experience with the products and context of the class. In our manual analysis, we biased toward assuming each phrase began with a verb.

3.5.3 The Unique Functions Metric. The number of unique functions refers to the number of functions that are semantically different in an individual's function tree. Functions created by the participants are manually grouped based on semantic similarity and observations in the class. This is different than simply omitting identical phrases. By using semantic similarity, we can distinguish functions whose meanings may overlap with similar functions but indicate a different part, step in the operation, or purpose. This metric is used because it allows us to get an idea of how well the participant understood the device. This metric is very expensive to generate and relies heavily on the experience of the coder to decipher natural-language meanings.

The subjectivity of this metric is similar to that of an ethnographic research approach. In our analysis, we biased ourselves toward considering all phrases as distinct. We only grouped them if there was clear evidence that they described the same function and corresponded to the same structure as another phrase.

We also did not attempt to create a master tree and compare the trees to this template. The reason we did not do this is there is no a single, unique solution that is most appropriate [13,14] and doing so would make the experiment prone to errors of omission by the researchers who prepare the tree. Instead, we used the number of unique functions as a relative measure to compare each participant with the others.

3.6 Controlled Variables and Covariates. We held several variables constant in our study. Since we considered each function identification method to be independent of the diagram used, we held the diagram type as constant. We chose the function tree as the fixed diagram type. We chose the tree over other types because engineers tend to mix and match methods [9]. We also controlled for variations in instruction by having a researcher provide the intervention, rather than the class instructors. Further, the amount of time and emphasis placed on each set of instructions was held constant for each method. We could not control other variables, and so we recorded these as covariates. These are:

- class level: freshman, sophomore, junior, or senior
- how often participant dissects things on their own: never/rarely, sometimes, often
- prior experience with dissecting this product: yes/no
- learned functional decomposition before: yes/no

3.7 Analysis Procedure. We followed a specific process to gather and synthesize the data prior to the statistical and qualitative analyses. This began by transcribing the function diagrams and surveys into EXCEL. Then, we used the following steps:

(1) Convert each function tree into an outline numeral system (e.g., root node = B7, branch nodes = B7.1, B7.2, etc.). If a branch is not connected to the tree, put an "x" in place of the parent indicator (e.g., B7.X.1).
(2) Determine the part of speech (POS) of the first word of every phrase using WORDNET. When a POS is ambiguous (e.g., "drill"), assume verb unless the context clearly shows otherwise (see Table 5).
(3) Determine the unique functions manually
    (a) Group all phrases by similar meaning and define a label for each function group
    (b) Review each group type for repetitions, and combine groups if meaning is repeated
    (c) Sort all functions by group and review each phrase to make sure all phrases in the group share the same meaning. Split groups into two meanings as necessary (Table 6).
    (d) Sort all functions by tree and review each phrase to make sure its assigned meaning fits its context. Define new groups if necessary (Table 7).
    (e) Repeat steps (c) and (d) at least three times.

After we conducted the semantic grouping, we calculated the nongraph metrics per participant, per session (i.e., vertices, number of unique functions, errors, error rate per level, etc.). In order to calculate the graph metrics (AGD and MGD), we used NODEXL, a plug in for EXCEL. Since the graph metrics require a complete diagram, we inserted blank nodes or unconnected branches using a placeholder node.

4 Quantitative Results

Several examples of the function trees produced by students are found in Fig. 4. Examples of data from a few other participants can be found in Table 8. Since a within-subject experimental design was used, a general linear model was performed in SAS with the session group and the device/week factor as blocking factors. Only main effects were considered.

Assumptions for analysis of variance (ANOVA) were met for most variables, based on tests in SPSS. A few variables are borderline-normal, but we treat them as normal anyway. The

Table 5 Examples of functions and the POS associated with the first word of the node

Func. ID	Submitted phrase	POS
B9.1	Meow	Blank
C3.3.2	Protective screens and housing	Adj.
B8	Drill	Verb
A6.1.1.1	Switch directions	Verb
C1.3.1	Switch moves back and forth	Noun

Table 6 Vertices sorted by generalized functions

Func. ID	Submitted phrase	Func. group
B12.1.3	Push air out by propeller	Move air
B13.1	Intake air	Move air
B14.1	Provide air	Move air
A1	Provide a flow of heated air	Move hot air
A2	Supply hot warm air	Move hot air
A7.2	Eject hot air	Move hot air

Table 7 A portion of the function tree for participant B2. Node B2.2.1.1 was changed from "control flow rate" due to context.

Func. ID	Submitted phrase	Function group
B2.1	Provide comfort	Spread forces over hand
B2.2	Move air	Move air
B2.2.1	Input air	Move air
B2.2.1.1	Turn on fan	Drive fan
B2.2.1.1.1	Spin blades	Drive fan
B2.2.2	Output air	Move air
B2.2.3	Adjust air flow	Control flow rate

near-normal variables have a higher chance of detecting a statistical difference where there is none [48]. Due to this, there is a slightly increased risk of a type-I error for the vertices metric. Assuming an alpha of 0.05, all the dependent variables except the number of vertices met the variance criteria. Since the dependent variables are probably not independent of each other, we analyzed each separately to satisfy the independence assumption.

4.1 ANOVA Results and Discussion. There are no significant effects by the method used on most of the measured responses (alpha = 0.05, see Table 9). Effect size is not reported since the sample size ($n = 78$) is less than 100 and statistical significance is not sufficiently affected by n. There is a significant difference in the number of functions on level 3 ($p = 0.035$) and a nearly significant difference for the MGD ($p = 0.051$). With more samples, these may test as significant. However, the differences in the functions on each tree level are probably meaningless since consecutive levels were not significant as well. Also, there does not appear to be any practical difference between the averages for each method (see Table 10).

A few covariates were significant ($p < 0.05$) or near-significant ($0.05 < p < 0.10$). Those who had taken the device apart before also perceived the activity as less useful ($p = 0.045$). These also made more syntax errors ($p = 0.003$), such as naming parts. However, these results are probably less meaningful since related metrics are not significant, such as error rate and unique functions. The error ratio by class level ($p = 0.071$) was near-significant. We observed that the syntax error rate was 18.4% for second year students, 14.7% for third year, and 5.4% for fourth year. However, class level did not produce a difference in the raw number of errors. This variable may become significant with more data or a population with a wider range of experience. Additionally, more than half the participants (14) reported not having learned functional decomposition before. Many of these were juniors and seniors, who had been taught functional decomposition in a required sophomore design class. This supports findings that engineering students often forget methods demonstrated early in their education [49].

Table 8 An excerpt of data gathered for three participants. TD, top-down; EN, enumeration; EF, energy-flow.

Participant code	A7	B2	C3
Method	TD	EN	EF
Class level	Sen.	Jun.	Soph.
Dissect things on own?	Rarely	Rarely	Often
Taken apart device before?	No	No	No
Used func. decomp. before?	No	No	No
Postsurvey	5	5	9
Unique functions	7	7	12
Vertices	13	14	16
Edges	12	13	15
MGD	8	7	4
AGD	3	3.18	2.69
Syntax errors	0	0	9
% Syntax error	0.0%	0%	56.3%
Functions level 1	1	0	1
Functions level 2	3	2	4
Functions level 3	5	5	11
Errors level 1	0%	0	0
Errors level 2	0	0	0
Errors level 3	0	0	9

Table 9 Significance of main effects (methods) on various dependent variables. Nonsignificant level responses omitted. Significant values in dark gray and near significant values in light gray.

Response	DF	*F* value	*P* value
Vertices	2	0.7	0.504
Uniq. func.	2	0.21	0.815
Efficiency	2	0.17	0.847
MGD	2	3.21	0.051
AGD	2	2.21	0.122
Errors	2	0.47	0.631
Error Ratio	2	0.85	0.436
Func. Lvl 3	2	3.65	0.035
Func. Lvl 6	2	2.58	0.088
Postsurvey	2	0.55	0.582

Table 10 Average values by method for selected variables. EF, energy-flow; TD, top-down; EN, enumeration.

	Vert.	Uniq. Fn.	Eff. (%)	MGD	Err. Rt. (%)
EF	11.57	9.32	77.68	4.780	17.37
TD	12.95	9.20	75.93	4.959	12.37
EN	13.24	9.52	78.24	6.115	12.73

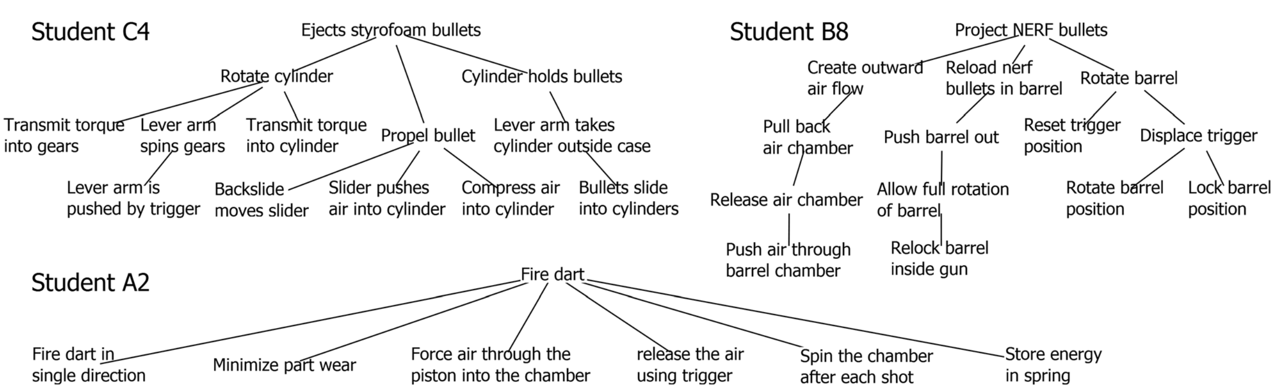

Fig. 4 These three function trees are digitized submissions of raw data collected from three participants. All three of these trees are for the toy dart gun, but each tree is generated using a different function identification strategy.

We did detect a possible learning effect over the testing period; however, this effect cannot be distinguished from the effects due to the device. The tree efficiency increased each week ($p < 0.0001$) from 65.7% to 79.8% to 86.3% in the last week. However, the error rate and other significant measures did not show a consistent trend. This may correspond to prior findings that practice improves performance [36].

4.2 Hypotheses Summaries. Hypotheses H1–H3 are rejected because there is not enough evidence that there is a significant difference due to the method used. If there were undetected statistical biases in the analysis, these would be likely to produce a false difference [48]. The *p*-values for these tests are high enough to fail to reject the null hypothesis. The error rate committed by different class levels decreased with more experience, but the result is above the 0.05 level ($p = 0.0706$). The practical difference between these is significant. Thus, we would expect a statistical difference with a larger sample size. H4 is tentatively accepted:

- H0: (failed to reject) there is no difference between the energy-flow, top-down, and enumeration methods
- H1: (rejected) there is a difference between the energy-flow and top-down methods
- H2: (rejected) there is a difference between the energy-flow and enumeration methods
- H3: (rejected) there is a difference between the top-down and enumeration methods
- H4: (tentatively accepted) the more experienced students will perform better than the less experienced students

This result differs slightly with that of Eckert et al. In their study, they found that professional designers using top-down and energy-flow approaches found more functions than enumeration approaches [9]. This seems to indicate that level of expertise is an important effect when evaluating the different methods.

5 Qualitative Results and Discussion

The second research question was explored by asking participants what was the hardest part of the dissection activity. The participant responses were qualitatively categorized by content and compiled into a few categories describing the nature of the comment. We report the percent students who made a particular comment in Secs. 5.1 through 5.7. We also exclude discussion of 46.8% of the comments, as these have to do with the physical disassembly, such as frustration with stripped screws, or having difficulty keeping parts from rolling off the table.

5.1 Difficulty With Generating Functions—18.2%. The most numerous comments related to functional decomposition described difficulty with generating functions. Among this group, students often described the difficulty of breaking a parent function into children functions. One student reported difficulty with "Coming up with subfunctions and sub-subfunctions."

5.2 Difficulty With Diagramming—13.0%. Many other participants also commented that the hardest part about the session was "the function tree." Some said, "I understand the components by taking it apart, not by writing about it." Another said, "I really don't like this. It's much easier for me to just write it down in traditional writing or explaining it to somebody. I'm always just worried about if I'm doing it right."

These individuals seemed to be inhibited by the requirement to create a diagram. Also, we had encouraged students to create rough drafts, but we found very few of these. It seemed most students preferred to do the tree in one step, or reorganize in their head. This seemed quite difficult in the case of energy-flow, since energy-flow is better with horizontal (flow) diagrams than vertical ones (trees) [29] and may have added an extra mental step. This may have been alleviated if students had been given multiple diagram types to work with, or if rough drafts had been enforced.

5.3 Difficulty With the Syntax—6.5%. We observed that many students struggled maintaining the verb-phrase syntax. Often, participants conflated parts and functions, despite a strong emphasis on distinguishing between parts and functions during the instructions. Some reported struggling with "Separating statements about what components are in the device from function statements." It seems that the functions associated with certain parts are so obvious that engineers find it difficult or superfluous to create a function-phrase to describe it (e.g., "motor" versus "generate rotational forces").

Related to this, some student struggled with "coming up with good verbs to describe functions." It seems that they did not use the list of common function verbs provided [33]. This seems to indirectly correspond with findings that reduced function taxonomies lead to easier use and interpretability [33]. In a different study of ours, whose data are not presented in this paper, we asked one student why he did not use the list. He said he had forgotten it was even there. This study did not explore why these lists were not used, but this would be for future work.

5.4 Difficulty With the Methods—6.1%. While few participants commented on the function identification methods, one brought up that "(I) did not understand the distinction between the last approach (enumeration) and this one (top-down)." Another described difficulty with "recognizing what the energy-flow is (i.e., tracing the energy-flow) in the NERF gun." These comments suggest that the identification methods may not have been sufficiently clear for the participants, though it is hard to say how common this was. Many participants did not seem to understand the energy-flow method well, although there is evidence that many attempted to identify flows through the device.

5.5 Scope of the Diagram and Stopping Point—3.7%. Many participants struggled with knowing the scope of the assignment. Some mentioned "trying to decide what is worth mentioning." One struggled with "Knowing when a function was decomposed fully—(it) seems to just keep going." There seemed to be a general sense that too great of detail was not necessary. Dym and Little state that diagrams do not need to be too detailed, and doing so may not improve functional understanding [15]. This may also correspond with too many functions inhibiting the interpretability of the tree [33]. Most of the participants that made comments of this nature also produced large and complete function trees, with very few syntax errors. These trees were among the best submitted.

5.6 Mechanical and Electrical Components—3.9%. 3.9% of participants reported difficulty with understanding mechanical and electrical components. Some of this may simply be due to the lack of exposure to hardware among lower class years. This seems to suggest that engineers with less experience with hardware and components would have a more difficult time analyzing a device. This corresponds with findings that younger engineers struggle more with identifying parts [9].

5.7 Other Issues Reported—11.7%. We also observed that some students did not see the point of functional decomposition, sometimes complaining about it. This corresponds with prior papers on this topic [5]. In this particular experiment, this could also have to do with the particular motivations the students had in participating. Several students had taken the class to have fun, and the additional workload may have seemed a burden to some of them.

The study did not find qualitative differences between the functions trees generated by each method. Each method seemed equally likely to produce a core set of functions. The diagram types found in each method were also similar to the others. Overall, there is not enough qualitative evidence to conclude that there is a difference between the trees generated by the various methods. This supports the quantitative results from this study.

6 Implications

These results imply that top-down, enumeration, and energy-flow methods perform the same for novice designers. Since some of these methods take significantly more effort to learn, this further implies that simpler methods are preferable at an early stage of learning design. There may be several reasons for why no difference was found between the methods: prohibitive cognitive loads, lack of mechanical knowledge, lack of practice using the methods, mental set fixation, or any combination of these. Additionally, for some students, certain methods may be harder to use because they conflict with their learning style. Also, if product complexity is a factor, it may be that certain functional decomposition methods work better for complex products than for simpler ones (as used in this study), or designs which are not mature and are still developing. On the other hand, these methods may also perform the same for either of these situations.

6.1 Cognitive Loads. The students described several tasks which were especially difficult, which may signify high cognitive loads. These include generating functions, diagramming, distinguishing parts from functions, and understanding the methods. Cognitive load theory may explain some of these observed problems. There are three categories of cognitive load [50]. Intrinsic cognitive load (ICL) is high when the complexity of the task is high. Extraneous cognitive load (ECL) results when the learning material is difficult to follow. Germane cognitive load (GCL) represents the level of expert skill.

It is most likely that each of these played a part in the observed effects [51]. We observed many students attempted to generate functions in one step, without creating a rough draft. This probably contributed to cognitive load. The students complained of both not knowing some parts and having difficulty with creating the tree, forming verbs, etc., corresponding with a ICL effect [4]. Low motivation also contributes to a high ICL, and it is possible that this affected the student performance [5]. Some students also complained that they did not understand the methods, and our instructional period may not have been sufficient, as mentioned before. This would contribute to the ECL. It is also possible that when students did not understand a method for identifying functions, they made their own [52].

Finally, the lack of expertise, lack of familiarity with the method, and abstract nature of the task would all contribute to the GCL [12]. One evidence of this is that Eckert et al. found that top-down and energy-flow approaches generated more functions than enumeration approaches [9]. They also report that those who used systematic methods identified new functions at a steady pace, whereas those who used enumeration identified functions all at the beginning or at the end of the session. Because we collected our data in bulk, we do not have temporal data associated with each function. However, based on the results from Eckert et al., we hypothesize that at low levels of expertise, the rate at which functions are identified is equally inconsistent between methods.

6.2 Instruction Methods. Since our instruction followed the interventions used at many universities, and those described in textbooks, this study may suggest the need to revise these models. Specifically, changes should include more discussion of the difference between functions and other types of information, such as design requirements or part names. This can be reinforced using practice [50] and guided examples [36,50].

6.3 Purpose of Task and Complexity of Product. The purpose of the task and product complexity may have influenced our results. Since the purpose of the task was to understand "how it works," it is possible that the effort many students put forward was superficial. Also, the products may not have been complex enough to benefit from more systematic methods like energy-flow or top-down. However, this may also indicate that for this type of task, a complicated function diagram is not necessary [1].

If these explanations are true, further studies would be needed to distinguish what activities need a certain level of detail, method, or type of diagram. We do not expect that functional decomposition methods would behave the same in a design task as it would in a product dissection task. These methods probably also perform differently under different parameters (see Table 1). Diagram types probably perform differently. In the study by Nagel et al., for example, function diagrams were judged on the basis of completeness and conservation of flows [36]. This level of rigor may not be necessary before ideation [1,15]. However, a comprehensive flow block diagram may be more appropriate than a tree or a list during detailed design after a concept has been chosen or when reverse engineering a competitor's product.

6.4 Other Implications. In this study, it was seen that participants tend to fixate on the name of the part, rather than actually determining its function or meaning within the entire system. For some parts, the name itself may imply the function (e.g., "motor") and may lead some engineers to simply write the part name instead of translating it into a function. This may be further compounded by known parts that have unknown or assumed functions. Therefore, the students may have seen a part and simply ignored its functions because they already felt they had a grasp on what it does. This seems to correspond to a tendency in young children to name and categorize unknown objects by their functions or purpose [53,54]. While untested, it is reasonable to hypothesize that the fixation on part names is a vestige of this early developmental cognition.

Another possible reason for the observed results is different methods may perform better for people with certain learning styles. Since functional decomposition is a form of abstraction [1,15] and abstraction is the deepest level of learning [4], it follows that learning styles may have an effect on individual performance with a particular method. Other possible explanations include mental-set fixation [3], which could potentially reduce performance over a long session. However, we did not have any clear indication that this was occurring in our study.

7 Conclusions

The results of this study suggest that for novices doing product dissection, there is no difference between energy-flow, top-down, and enumeration methods for identifying functions. For design theory, this suggests that any method is equally effective at low levels of expertise, but enumeration should be avoided because it leads to fewer identified functions at higher levels of expertise [9]. Our data point to a high cognitive load in novice engineers using functional decomposition. Based on this conclusion, we recommend any systematic methods, such as top-down or energy-flow, for design education and practice. However, for future studies of product dissection with novice engineers, it appears that the method used to identify functions is not a significant factor.

The cognitive load in novices seems to obscure differences between the methods. This may be due to a few reasons. Our survey data may point to a lack of expertise with the methods and/or a lack of experience with the components. Other explanations include the complexity of the artifact and the instruction on how to use the methods [36]. For example, it is possible that some students did not understand a method and made their own up [52]. It is also possible that for the purpose of simply understanding how something works, each method will perform the same.

The survey results also have implications for education. Participants reported difficulty with generating functions and drawing a diagram. We also observed that there was a high rate of confusing functions with part names or design requirements. These issues suggest that students do not understand the distinction between a function and a design requirement, or how to translate between the two. Based on these results, we recommend additional training on how to use diagrams to map out different design ideas. We also recommend focusing on the concepts of functionality and diagramming first and introduce specific identification methods later.

There are some limitations to this study. The results of this study should not be extended to other design tasks, levels of expertise, or other parameters levels from Table 1. In addition, this study only used one type of diagram, which may have imposed too much extra work when using the energy-flow or enumeration methods. Additionally, the statistical analysis cannot separate the effects due to time/learning and the effects due to the artifacts. Finally, the purpose of the task used in this study was to create a generic description of a product. This may have affected the quality of the diagrams. Other studies argue for the merit of functional modeling in a specific design context, such as defining a mechanical design space [34], decision making [55], or satisfying customer needs [56].

The results of this work can improve future studies on cognition during functional decomposition. Future work should focus on determining (1) how different levels of expertise affect cognitive load and the rate of function identification [9], (2) how different diagrams work in conjunction with each method, (3) how these methods perform in other design tasks. Future studies should also explore improving instruction for functional decomposition. Table 1 shows the parameters laid out for this study and the levels we chose. We recommend that future researchers use these or similar parameters to define their studies so future work in decomposition can be compared, and we can identify gaps in knowledge, pedagogy, and theory. We also noted that many students used phrases that are not strictly functions. We recommend that future studies make particular emphasis on the difference between function and other types of information, such as requirements or user actions.

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